CENTER FOR DECISION RESEARCH

Ambiguity and Actuaries: A survey
of members of the Casualty Actuarial Society

Report prepared by

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Center for Decision Research

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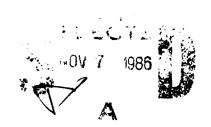Center for Decision Research

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This report is a non-technical summary of the results of a survey of the Casualty Actuarial Society conducted to test implications of Einhorn and Hogarth's (1985) ambiguity model with a population of expert subjects (professional actuaries). The survey instrument required responses to different scenarios in the form of either insurance premiums or willingness to trade to be made in the role of either a buyer or seller of insurance. The presence or absence of ambiguity was manipulated by different versions of the scenarios that either emphasized uncertainty concerning probability estimates (the ambiguous case) or estimates that were reliable (the non-ambiguous case). In addition, probabilities of potential losses were varied across scenarios. Each respondent saw three of five different scenarios although some were asked to respond to two versions of specific scenarios. Questionnaires were sent to all 1,165 members of the Casualty Actuarial Society resident in North America in January and February 1986. The number of usable responses was 484 (42%).

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19. abstract

Results were largely supportive of the Einhorn-Hogarth model: (1) Actuaries' pricing decisions are sensitive to the presence of ambiguity, in both the roles of buyers and sellers. (2) Sensitivity to ambiguity is consistent with the predictions of the ambiguity model: (a) ambiguity avoidance was greatest for small probabilities of loss and decreased as probabilities of loss increased (holding all else constant); and (b) actuaries playing the role of sellers exhibited greater ambiguity avoidance than those taking the role of buyers. In addition, actuaries taking the role of buyers exhibited ambiguity preference for high probability of loss events (p = .90). Additional findings were: (1) Ambiguity interacted with the size of the potential loss in the one scenario where this was manipulated: (2) Actuaries' responses to ambiguity are qualitatively similar to other groups surveyed (MBA and undergraduate business students as well as business executives). (3) Actuaries' responses do, however, differ quantitatively from the other groups. In short, actuaries are more cautious. Results of the survey emphasize the importance of ambiguity in decision making under uncertainty and also serve to question the manner in which insurance decision making has been typically conceptualized by economists.

Ambiguity and actuaries:
A survey of members of the Casualty Actuarial Society

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1. Purpose of study

1.1 *Background*

It is axiomatic that probabilities assigned to complementary events should sum to one. For example, denoting the probabilities of heads and tails appearing on any given coin toss by p(H) and p(T), respectively, the basic rule of probability theory states that p(H) + p(T) = 1.0. Moreover, in situations more complex than coin tossing, and particularly where probabilities are not "known" a priori, this rule is often used to infer whether decisions made under uncertainty do or do not accord with economic principles of rational behavior.

The possibility that people would willingly violate this rule in their actual decisions was originally tested in some ingenious examples published by Daniel Ellsberg* in 1961. Ellsberg presented his subjects (who included some of the foremost statisticians and economists of the time) with problems of the following kind.

Imagine two urns, each containing red and black balls. Although it is known that Urn 1 contains 100 balls, the proportions of red and black balls are unknown. Urn 2, on the other hand, contains 50 red and 50 black balls. Furthermore, imagine that you can win $100 by naming the appropriate color (red or black) of a ball to be drawn at random from Urn 1. Would you bet on red, bet on black, or be indifferent between red and black? What would your answer be if the drawing were to be made from Urn 2?

Next imagine that you stand to win $100 if a red ball is drawn from an urn. However, this time you must state whether the drawing should be made from Urn 1, from Urn 2, or whether you would be indifferent between the urns. What would you choose if the prize depended on drawing a black ball from one of the urns?

On considering these questions, most people are indifferent between red or black when a ball is to be drawn from either Urn 1 or Urn 2. However, when asked to choose between the urns, the majority favor Urn 2 whether the prize depends on drawing either a red or black ball. In other words, despite the fact that responses to the questions involving choices *within* urns indicate assessing the same probability (.5) to both red and black, choices *between* urns imply a greater probability in Urn 2 compared to Urn 1 for drawing a ball of the appropriate color. However, given that there only two mutually exclusive colors, these latter assessments *must violate the rules* of probability theory.

Ellsberg's examples showed that, in simple choices involving urns, people's decisions are affected not only by the probabilities of events, but the degree of uncertainty surrounding their

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* This is the same Daniel Ellsberg who subsequently attracted attention for his role concerning the "Pentagon papers".

estimates of these probabilities. Moreover, this latter form of uncertainty -- which Ellsberg called ambiguity -- can lead people to violate fundamental principles of rational economic behavior. Ellsberg did not, however, test the extent to which the behavior he observed generalized to situations beyond bets involving hypothetical urns although he did speculate about how ambiguity might affect different types of economic decisions.

Since the publication of Ellsberg's paper, a number of investigators have confirmed people's tendencies to avoid ambiguous probabilities. However, for the most part, experimental work has been limited to examining choices involving gambles among urns using positive payoffs (i.e., situations involving potential gains as opposed to losses). Moreover, published work has been almost exclusively focussed on situations where people avoid ambiguity and has failed to consider the notion that, in some circumstances, people might actually prefer making choices with ambiguous as opposed to non-ambiguous probabilities.

1.2 *Ambiguity and insurance*

For several reasons, the market for insurance is a natural place to examine the effects of ambiguity. First, both insurance firms and consumers are confronted with events involving varying degrees of ambiguity. Contrast , for example, the use of probabilities inferred from "life" tables, on the one hand, with those assessed for the less familiar risks of modern technology such as satellite launches, on the other. Second, economic theory makes relatively "simple" predictions concerning the operation of insurance markets. Third, insurance is an important part of economic activity with ramifications in many parts of daily life.

1.3 *Prior work*

Recently, in collaboration with Hillel J. Einhorn of the University of Chicago and Howard Kunreuther of the University of Pennsylvania, the author has been investigating the implications of Ellsberg's original insights to phenomena with real economic consequences. This program of research has involved three phases: (1) development of a quantitative model that can be used to describe *how* people assess probabilities in ambiguous circumstances; (2) testing of the model's predictions in controlled laboratory experiments; and (3) extensions of predictions and implications of the model to real world phenomena.

For the reasons enumerated above, we have chosen to examine the implications of our model for insurance markets and have already published some preliminary reports on this topic. (See Appendix A). In the experimental part of this work, we have asked people to respond, in the role of consumers or insurance firms, to hypothetical scenarios about insurance in which we have systematically varied the information base to manipulate both probabilities of specific losses and the

degree of ambiguity concerning the probabilities of incurring losses. Respondents have been faced with two types of questions: (1) to state premiums they would be prepared to pay as consumers or charge as firms (maximum premiums for consumers, minimum premiums for firms); and/or (2) to state whether they would be prepared to buy or sell insurance at given prices suggested in the questionnaires. Whereas the experimental results have generally provided positive evidence for our model, they can be criticized on the grounds that respondents are not well informed concerning the operation of insurance markets. On the one hand, this criticism is somewhat muted on the consumer side by the fact that many people who buy insurance of are not well informed. However, this is not the case for subjects who responded as if they represented insurance firms.

1.4 *Goals of present survey*

The major goal of the present survey was to study the effects of ambiguity by extending our examination of the predictions of the ambiguity model to a population of respondents with substantive expertise in insurance. Since professional actuaries are recognized authorities on this topic, we were delighted to be able to survey the membership of the Casualty Actuarial Society.

In addition to testing the ambiguity model as such, the survey described below also allowed us to consider the following issues: How do actuaries differ from the other groups we have surveyed on the same issues? How do actuaries react to ambiguity in the role of consumers and not just experts concerned with pricing, i.e., on the side of firms?

2. Description of survey

2.1 *The ambiguity model*

Many surveys of professional groups phrase questions in ways that allow reporting results in the form of percentages of respondents who agree or disagree with particular statements, or alternatively, distributions of responses are provided over different categories of responses. The present survey differs in that (a) our questions were guided by a specific model of how we thought people might react to ambiguity, and (b) we wished to adopt an experimental framework in which different groups of the respondent population would respond to different sets of questions.

To motivate the hypotheses guiding the survey, it is important to discuss the rationale underlying the ambiguity model. The intent is to describe *how* people assess probabilities in ambiguous circumstances, and the model is based on three principles. (1) People are first assumed to anchor on an initial probability denoted p. This anchor may be based on past experience, suggested by an analogous situation, or even be the figure provided by an expert. The anchor is then adjusted by imagining or mentally s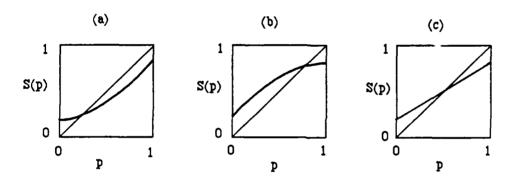imulating other values that the probabililty could take. (2) The greater the degree of ambiguity experienced, the larger the range of simulated probabilities.

(3) The weight given in imagination to alternative values of the probability that are greater or smaller than the anchor p depends on the individual's attitude toward ambiguity in the particular situation. For example, this attitude can be thought to reflect differential degrees of caution or optimism that influence a person's imagination when simulating what values are most likely.

The mathematical function that models this process (see Appendix B) describes the stated estimate of the ambiguous probability, S(p), as a two-parameter function of p, the initial anchor. These two parameters represent the amount of ambiguity perceived in the situation, and the person's attitude toward ambiguity in the circumstances. They are denoted by the symbols θ and β, respectively. To illustrate, Figure 1 shows three ambiguity functions that have the same θ parameters, but differ as to β.

Figure 1: Examples of ambiguity functions

The parameters of this model can be thought of as distorting the initial or anchor probabilities as follows. The amount of perceived ambiguity (θ) determines the extent to which S(p) varies from p over the range of the latter. Thus, when there is no perceived ambiguity, $\theta = 0$, and S(p) = p; however, as θ increases S(p) deviates more from p (or the diagonal in Figure 1). The parameter β reflects whether the net adjustments that people make to the anchor by imagining alternative values of the probability result in positive or negative deviations of S(p) from p. Thus, if acting cautiously when faced with the probability of a gain, the sign of the net adjustment will typically be negative (i.e., S(p) < p) over most of the range of p -- see Figure 1a. (The assumption here is that costs of errors are perceived to be greater for positive than for negative deviations from the anchor value). On the other hand, the adjustment is more likely to be positive (i.e., S(p) > p) for assessments concerning losses -- see Figure 1b. In some cases, people may be equally concerned as to whether the deviations are positive or negative. This results in a situation such as that shown in Figure 1c

where the deviations from p are positive for p < .5 but negative for p > .5. More generally, β -- or the person's attitude toward ambiguity in the circumstances -- determines where the S(p) function crosses the diagonal and the ranges of p for which net adjustments are positive or negative.

2.2 *Hypotheses about insurance decisions*

How does the ambiguity model relate to insurance decision making? To consider this issue, first dichotomize probabilities of losses associated with insurance as being ambiguous or

Figure 2: Classification of insurance situations

| | Consumers | |
	Nonambiguous	Ambiguous
Nonambiguous	Well known processes (1)	Typical situation (2)
Ambiguous	New technologies -- inside information for consumers (3)	New technologies -- processes poorly understood (4)

Firms

non-ambiguous and consider the viewpoints of both insurance firms and consumers. This can be illustrated by the 2x2 table shown in Figure 2 above.
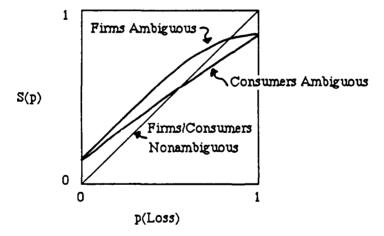
Cell 1 of Figure 2 represents cases where both consumers and firms are non-ambiguous. Examples of this kind of situation might be certain kinds of industrial insurance where both consumers (in this case industries) and insurance firms have much experience with the risks involved. Commercial aviation, for example, could be representative of this cell. Cell 2 represents a familiar case exemplified by, say, life or automobile insurance. Here insurance firms have precise statistics based on much experience; individual consumers, however, typically rely on their own limited experience or that of acquaintances and have only vague notions of the probabilities of losses. Cell 3 could be represented by a situation involving new technologies where those proposing the technology feel far more confident about the risks than insurance companies who are being asked to face them for the first time. In cell 4 situations, both consumers and firms are ambiguous about the probability of losses.

In terms of the ambiguity model, one would expect the S(p) functions of both firms and consumers to be equal to p (the anchor probability) in the cases where both are not ambiguous about the probability of a loss. However, we hypothesized that the ambiguity functions of firms and consumers would differ significantly under ambiguity. Specifically, our hypothesis was that -- holding ambiguity constant -- insurance firms would be more cautious in ambiguous circumstances than consumers with the result that the ambiguity or S(p) function for firms would lie uniformly above that of consumers as illustrated in Figure 3 below. The rationale is that when taking on or assuming a risk one is likely to accord more weight in imagination to probabilities of loss greater than the anchor value than those who are transferring the risk to others.

If one assumes that prices for insurance are functions of firms' and consumers' S(p) values, our hypotheses can be stated more explicitly as implying the following pattern of results:

(1)   Prices for insurance required by firms will be sensitive to ambiguity about probabilities. However, sensitivity will be greatest in a relative sense at low probabilities and decrease as the probabilities for losses increase. One would not

Figure 3: Approximate ambiguity functions for consumers and firms

expect, however, that firms would offer insurance for ambiguous events at prices below the corresponding non-ambiguous events.

(2)   Prices consumers are prepared to pay for ambiguity will also be sensitive to ambiguity. Moreover, like firms, consumers' sensitivity to ambiguity will decrease in a relative sense as probabilities of losses increase. Unlike insurance firms, however, we expect

consumers to show ambiguity seeking for high probability of loss events. This will be evidenced by willingness to pay less for insurance under ambiguous as opposed to non-ambiguous conditions for high probability of loss events.

In the various studies of which the survey was comprised, we actually investigated a number of additional issues. However, these will be discussed in relation to the particular studies.

2.3 *Survey design*

In designing the survey, we adhered to the same methodology used with other groups of respondents. Specifically, this involved short scenarios which requested responses in the form of prices for insurance (as firms or consumers) and/or indications of willingness to trade at specific prices. We employed five different basic scenarios (to be described below), three of which had been used in previous studies with other groups and two which were designed specifically for this survey.

All scenarios were pre-tested with practicising actuaries prior to use in the study. First, several sessions of pilot testing took place with two groups of actuaries in Chicago. Second, all scenarios were subject to scrutiny by officials of the Casualty Actuarial Society. The results of these tests led to minor modifications to the scenarios previously used with other groups (to avoid possible ambiguities in interpretation), but more substantial changes to the new scenarios. In designing the scenarios, we were faced with a trade-off between providing respondents with the kind of detailed background information that would normally accompany knowledge of actuarial cases and making the scenarios short enough so that members of a busy profession would not be discouraged from responding. Moreover, being concerned about the amount of time one could reasonably ask of respondents, we limited our requests for responses to at most three different scenarios (although some respondents were asked to answer different versions of the same basic scenarios). The goal was to limit the necessary response time to a maximum of 15 minutes.

The population of actuaries consisted of the 1,165 members of the Casualty Actuarial Society who, according to the Society's records, were resident in the United States and Canada in January 1986. Members of this population were allocated at random to different subgroups that we formed to take account of (a) the restriction that each respondent could only answer at most three scenarios and (b) the design of the particular experiments that were nested within each scenario (to be described below).

Questionnaires were mailed in January and February 1986, with stamped addressed envelopes provided to facilitate returns. A general letter signed by the author requesting participation in a study on risky decision making was preceded in the questionnaire materials by a letter from the Vice-President for Development of the Casualty Actuarial Society that also urged the

membership to participate. The scenarios for each subgroup appeared on different sheets of paper that had been stapled together in booklet form. Spaces for responses were provided and indicated on the sheets. Respondents were told that they would "find a number of questions related to the pricing of insurance and warranties in different scenarios". They were requested to answer the questions in the order in which they appeared. In addition, to standardize interpretation, they were explicitly told that use of the words *pure premium* in the questions should be understood as meaning premiums *exclusive of all loss adjustment and underwriting expenses*. Respondents were also asked to indicate their "length of experience as an actuary, in number of years".

Since responses were anonymous, a postcard was mailed to all members of the population in March 1986 with the dual purpose of thanking those who had already responded and enjoining those who had yet to reply to return their questionnaires. From the population of 1,165 names on the mailing list, we finally received 484 usable responses (42%). Of those responding, 377 answered the question in respect of length of experience as an actuary. The mean of this distribution was 13.8 years (median 12 years) with a range of from 1 to 50 years.

3. The studies and results: An overview

3.1 *Preliminary comments*

The results of the survey are difficult to present in that they essentially involve experiments involving five different scenarios with different designs within each scenario. Thus, to help the reader digest the results, we have decided on the following tactic. In this section of the report, we present in respect of each scenario: (a) a synopsis of the basic scenario; (b) variations on the scenario that were used to manipulate different variables; (c) qualitative statements concerning the results of the experiments; (d) qualitative statements concerning comparisons of results with other groups that have responded to the same questions. The focus of this section of the report will therefore not be statistical although the conclusions reached are based on the use of appropriate statistical tests of the data. Statistical summaries of the results of the different experiments are, however, provided in Appendix C.

There were five basic scenarios. We refer to these as: *The Defective Product* ; *Brown River* ; *Palcam*; *Computeez* ; and *Health*. The *Computeez* and *Health* scenarios were those specifically designed for this survey.

3.2 *The Defective Product*

a. Basic scenario: The owner of a small business with net assets of $ 110,000 seeks to insure against a $ 100,000 loss that could result from claims concerning a defective product.

b. Variations: Respondents were asked to consider this case either from the viewpoint of the

owner of the small business (i.e., consumer) or to imagine that they headed a department in a large insurance company (i.e., firm) who was authorized to set premiums for the level of risk involved.

Ambiguity was manipulated by factors involving how well the manufacturing process was understood, whether the reliabilities of the machines used in the process were known, and the state of the manufacturing records. A comment was also added as to whether one could "feel confident" (non-ambiguous case) or "experience considerable uncertainty" (ambiguous case) concerning an estimate of the probability of loss that was provided (to serve as the anchor value).

Various (anchor) probabilities of loss were provided for this scenario ranging from .01 to .90. For the most part, required responses were in the form of *pure premiums* (maximum for consumers, minimum for firms). Some respondents saw both the ambiguous and non-ambiguous versions of the scenario in a given role (consumer or firm); others were required to respond to at most two probability levels (but in a given role and state of ambiguity); others were asked whether they would be prepared to trade at given prices (as consumers or firms, in ambiguous or non-ambiguous condtions).

c. Results: 351 actuaries provided usable responses for this study. The experimental results provided strong support for the predictions of the ambiguity model.

* Premiums were sensitive to ambiguity. In short, premiums were generally higher in ambiguous compared to non-ambiguous circumstances *but* with important exceptions noted below.

* Both consumers and firms showed decreasing sensitivity to ambiguity as probabilities of losses increased.

* Consumers and firms differed in their reactions to ambiguity. Specifically, firms were more sensitive to ambiguity than consumers. Also, whereas for high probability of loss events consumers were ambiguity *seeking* (i.e., willing to pay more to insure against non-ambiguous as opposed to ambiguous risks), this was not the case for firms.

* Both consumers and firms showed sensitivity to ambiguity for the two types of questions asked, i.e., stating prices (pure premiums) and willingness to trade at given prices.

d. Comparisons with other groups: Other groups tested using this scenario include MBA students at the University of Chicago and executives attending different management programs (including a group of investment officers from life insurance companies). Of these groups, the most extensive and comparable data have been gathered from the MBA students. These comparisons reveal:

* Compared to the other groups, actuaries are similar in the directions and types of

reactions that they make toward ambiguity when simulating the roles of both consumers and firms.

* Actuaries differ from the other groups (and particularly MBA students) in that the prices they quote as firms or are prepared to pay as consumers are generally higher. This is particularly the case for low probability of loss events.

* When simulating consumers, actuaries differ from the MBA students in that the latter start to exhibit ambiguity seeking behavior for events with lower probabilities of losses. In other words, actuaries show ambiguity avoidance over a larger range of probabilities than the MBA students.

Quantitative summaries documenting the above results are provided in Tables C.1 and C.2 of Appendix C.

3.3 Brown River

a. Basic scenario: This also involved a small businessman, a loss of $ 100,000 and a large insurance company. In this case, the potential loss was contingent on the flooding of a warehouse "located on the Penndiana floodplain".

b. Variations: Respondents were asked to consider the case either from the viewpoint of the businessman or a large insurance company. However, in contrast to the Defective Product scenario, only one probability level was investigated (.01).

Respondents received either ambiguous or non-ambiguous versions of the stimuli but ambiguity was operationalized in a manner different from the previous scenario. In the non-ambiguous version, respondents were told that the probability of a flood destroying the inventory 'n the warehouse could be confidently estimated by experts on the basis of considerable hydrological data. In the ambiguous case, they were told that limited data existed concerning the flooding of the Brown River. Moreover, hydrologists were "sufficiently uncertain about this event so that this annual probability could range anywhere from zero to 1 in 50 (i.e., .02) depending on climatic conditions." Thus, although this scenario had an ambiguous condition, the range of ambiguity was restricted.

Two response modes were used: Stating prices (pure premiums) and indicating willingness to trade at given prices.

c. Results: 144 actuaries responded to this scenario.

* This scenario revealed *no* effects for ambiguity, either in the expression of prices in the form of pure premiums or in willingness to trade at given prices.

* Prices of actuaries given in the role of consumers tended to exceed those asked by actuaries playing the role of firms.

d. Comparisons with other groups: Other groups who have responded to these questions include business students at the University of Pennsylvania's Wharton School, and various groups of business executives.

* Using an experimental design similar to that described above, the other groups have (unlike the actuaries) shown a limited degree of sensitivity to ambiguity.

* Ambiguity has had a more marked effect on simulated firms as opposed to consumers in the non-actuary population.

Statistical information concerning the Brown River scenario is included in Tables C.3 and C.4 in Apppendix C.

3.4 *Palcam*

a. Basic scenario: This concerns the price of a warranty for a possible defect in a new personal computer called the Palcam-X. It would cost $ 400 to repair the defect should it occur.

b. Respondents were required to play the role of either the owner of a computer store who was about to start selling the Palcam-X or a customer who had already decided to buy a Palcam-X. Storeowners were told "this represents a potentially profitable addition to your product line and you hope to sell many of these computers". Storeowners were required to estimate what they would charge, and customers what they would pay, for a warranty to cover the defect. (This was assumed to be separate from the price of the Palcam-X itself).

There were ambiguous and non-ambiguous conditions. For the former it was stated that the design of the Palcam-X was new, experts disagreed concerning the chances of a defect occurring in the warranty period, and there had been insufficient time to assess the model's performance in regular use. Moreover, although an estimate of the chances of a breakdown was given, there was "considerable uncertainty about this estimate". On the other hand, in the non-ambiguous condition, the design was based on well-known principles, the model had been extensively tested, and experts agreed on the chances of a breakdown occurring in the warranty period. Respondents should thus "feel quite confident" in the estimate provided for the probability of a breakdown.

Three probabilities of breakdowns were investigated: .05, .25, and .75.

No respondent received more than one version of this scenario.

c. Results: 239 actuaries provided responses. These showed marked agreement with the predictions of the ambiguity model.

* In the non-ambiguous conditions, median responses of both consumers and firms (i.e., storeowners) were close to expected value (i.e., probability x potential loss). However, responses for firms were somewhat higher than consumers at all three probability levels.

* Consumers in the ambiguous condition, showed ambiguity avoidance (i.e., ambiguous price > non-ambiguous price) at the low probability level (.05), no ambiguity effect at the moderate level (.25), but distinct ambiguity seeking at the high level (.75).

* Ambiguity avoidance was exhibited by firms (storeowners) at the low probability level (.05), but there were no ambiguity effects at either .25 or .75.

d. Comparisons with other groups: A study using the same scenario and stimuli was conducted with a group of investment officers from life insurance companies ("life officers") attending a management development seminar. This study differed, however, in that although respondents took on the roles of either consumers or storeowners in ambiguous or non-ambiguous conditions, they gave responses for all three probability levels used above (i.e., .05, .25, .75).

* At a qualitative level, responses by the life officers were similar to the actuaries, viz, effects of ambiguity (as predicted by the ambiguity model) and higher median prices being demanded by storeowners than those offered by customers.

* At a quantitative level, the life officers playing the role of consumers were not willing to pay as much as the actuaries.

Further details on this scenario are provided in Table C.5 of Apppendix C.

3.5 *Computeez*

a. Basic scenario: Respondents were asked to assume the role of an actuary called in by Computeez, a manufacturer of personal computers, to determine the price of a one-year warranty on the performance of a new line of PC's to be put on the market during 1986. The warranty is to cover the failure of the XY component manufactured by Computeez. The cost of repairing a breakdown is $ 100 per unit in which it occurs. It is assumed that there can be at most one breakdown per unit during the warranty period.

b. Variations: These concerned (a) two levels of the number of units that Computeez expected to sell,viz., 10,000 and 100,000, (b) ambiguous versus non-ambiguous probabilities of breakdowns, (c) whether the risks of breakdowns associated with any computer were independent of other computers sold or would be common to all computers (i.e., the insured risks could either be independent across individual units or perfectly correlated), and (d) three different probability levels, .001, .01, and .10.

In the ambiguous versions of the scenario, respondents were told that experts were confused by the results of tests concerning the performance of the XY component, that there was considerable disagreement amongst the experts concerning the chances of breakdown, and that they should not be "at all confident in the accuracy" of their estimate of the probability of a breakdown.

On the other hand, in the non-ambiguous version experts had examined company records, conducted several independent tests of their own, and all agreed on the chances of the XY becoming defective within a year of purchase such that the probability of this event could be confidently estimated.

Independence of the probability of breakdown of the XY component in different computers was noted by stating that the nature of the potential flaw was random rather than systematic across computers such that its failure in any one computer was independent of failure in any others. Dependence, however, was indicated by saying that the potential flaw was due to a particular aspect of the manufacturing process. Moreover, the effect of this would be that if the XY component failed in any one E-Z computer, it would fail in all others as well.

Finally respondents were asked to state "What is the minimum pure premium you would recommend for the warranty (per unit sold) on the understanding that this will cover the $ 100 per unit cost of repairing the XY component if this fails within a year of purchase?"

c. Results: Each actuary in the survey received a copy of this scenario. This yielded some 480 valid responses which were spread over a research design that involved 24 different experimental conditions. Overall, and in accordance with the ambiguity model, actuaries were sensitive to the manipulation of ambiguity (in the appropriate direction). However, in this study we were particularly interested to see how ambiguity would interact with the other variables we manipulated in the research design. Appropriate statistical tests showed the following significant effects:

* There was a highly significant effect for ambiguity. Averaging across all conditions, the estimated premium was $ 9.14 per unit in the ambiguous situation and $ 6.43 in the non-ambiguous.

* Probability level -- as the probability of loss increased, so did the recommended premium (by itself a result that is hardly surprising or of interest in the context of this study). However, averaging across conditions, the increase was not linear, the premium at .001 being estimated at $ 1.94 per unit compared to $ 5.06 at .01, and $ 16.35 at .10.

* There was a large effect for type of risk. The average premium across conditions for independent risks was $ 5.25 per unit compared to $ 10.31 in the correlated case.

* Ambiguity interacts with the number of units to be sold. In the non-ambiguous case, the average price (across all other conditions) is estimated at about $ 6.50 per unit whether sales estimates had been given as 10,000 or 100,000 units. However, under ambiguity, these prices are roughly $ 7.70 at the 10,000 unit level and $ 10.60 at the 100,000 level.

*   There is a significant interaction between type of risk (independent or correlated) and level of probability. In short, the differences between premiums in the independent and correlated cases become larger (in a multiplicative as opposed to additive manner) as probability levels increase.

More detailed information on this particular study appears in Table C.6 of Appendix C.

3.6 Health

a. Basic scenario: Respondents were to assume the role of the chief actuary in a major health insurance company who was considering what additional annual premium to charge for complications arising from a certain surgical procedure. The cost of such complications (when they arose) averaged $ 100,000 and 100,000 people subscribed to the plan covering the procedure.

b. Variations: Ambiguity was varied in two ways. In one, respondents were told that since the particular surgical procedure was fairly new, there were only sketchy indications of how many operations were likely to be performed in the coming year and, of these, how many would lead to complications.However, the best estimate was 100. Moreover whereas a best estimate was also provided for the probability that any particular operation would lead to complications, respondents were told that they had "little confidence in the precision of these estimates".

The second form of ambiguity delimited the range of probabilities. Respondents were told that past data concerning both the incidence of the condition and the extent of complications requiring the additional surgery showed considerable variability. Indeed, the number could vary anywhere between 0 and 200. Moreover limits were provided on the probability of there being complications. Since the three levels of probability manipulated in this study were .05, .20, and .50, the corresponding limits were given as from .00 to .10, .10 to .30, and .40 to .60, respectively.

In the non-ambiguous version of the questionnaire, respondents were told that they had excellent data on both the incidence of the condition requiring the surgical procedure and the numbers of operations that involved complications. Moreover, they were told that they could be confident in their estimates that 100 people would require the operation and that, of these, complications could be expected to arise in a specified number of cases (which varied according to the probability level condition in the experiment).

c. Results: 181 responses were received for this scenario.

*   The study showed significant ambiguity effects with prices for the ambiguous scenarios exceeding the corresponding non-ambiguous versions, with one exception. (The exception concerned responses at the .05 level where only 11 responses were received in respect of the ambiguous condition with an uncertain point probability).

* Contrary to the predictions of the ambiguity model, sensitivity to ambiguity did not decrease as the probability levels increased.

* At both the .20 and .50 probability levels, there were no differences in prices between the two methods of operationalizing ambiguity, i.e., an uncertain point probability and specified ranges of probability. (This was not the case at .05 because of the anomalous result mentioned above).

Results of this scenario are presented in greater detail in Table C.7 of Appendix C.

4. Discussion

4.1 *General conclusions*

The major conclusion from this survey is that ambiguity does affect the pricing decisions of actuaries, both in the roles of consumers and firms. Moreover, although there are quantitative differences in the manner in which the actuaries in these studies differ from other groups we have surveyed (mainly MBA students and business executives), it is the qualitative similarity in responses that is most striking.

There are some exceptions to this general conclusion. First, the actuaries were not sensitive to the ambiguity manipulation in one of the scenarios (Brown River), and in a couple of cases, responses from subsets of actuaries appeared anomalous (this occurred in specific conditions in both The Defective Product and Health scenarios). Although it is easy to generate reasons after the fact, we note that, contrary to other scenarios, ambiguity was manipulated in the Brown River scenario as a fairly narrow band of uncertainty ($.00 \leq p \leq .02$). In addition, both anomalous results in the other studies arose from particularly small subsets of actuaries such that it is difficult to eliminate the hypothesis of sampling errors in these two cases.

There were basically two ways in which the responses of the actuaries differed quantitatively from those of other groups. First, prices quoted by actuaries were generally higher despite the fact that they had been explicitly instructed to specify *pure premiums* (this instruction was not given to the other groups). Moreover, higher prices were particularly marked for low probability of loss events and applied equally to events with ambiguous and non-ambiguous probabilities. (There was one exception to this generalization in the case of the Brown River scenario). Second, when playing the role of customers, actuaries exhibited behavior consistent with ambiguity avoidance over a wider range of probability of losses than the other groups. In other words, as probabilities of losses increased, the other groups showed a tendency to prefer rather than avoid ambiguous probabilities at lower values than the actuaries. It is interesting to speculate as to the possible reasons for these differences. One hypothesis is that, through training and experience, actuaries

learn to be more aware of the inherent imprecision of probability estimates; moreover, such imprecision is relatively greater the smaller the probabilities.

4.2 *Evaluating the ambiguity model*

It is one thing to say that the actuaries, like our other respondents, are sensitive to ambiguity, it is quite a different matter to say *how*. On the basis of the ambiguity model, we made two types of prediction that implied specific patterns of empirical results. These were, first, that for both firms and consumers ratios of ambiguous to non-ambiguous prices would be greater than one at low probabilities and decrease as probabilities of losses increased; and second, in the case of consumers, ambiguity preference (ratios less than one) would be observed for high probability of loss events. This pattern of predictions is implicit in Figure 3 which shows the ambiguity function for firms lying uniformly above that of consumers across the range of probabilities.

The predicted pattern of results could be fully tested with two scenarios The Defective Product and Palcam. In both cases, the predicted pattern was seen to hold although there was one small exception. This occurred at the low probability of loss events where the prices in the ambiguous conditions did not differ between firms and consumers (for the actuaries. This exception did not occur for the other groups surveyed).

Parenthetically, we note that probability levels were also manipulated in the Computeez and Health studies-- although these involved only low probability of loss events and the perspective of firms (but not consumers). The data from the Computeez study were consistent with declining ratios of ambiguous to nonambiguous prices as probabilities varied from .001 to .100, but in the Health study (where probabilities varied, in effect, between .00005 and .0005) no such effects were observed.

With one exception, our scenarios involved insurance concerning unique and/or independent events and held potential losses to a constant amount. For example, in The Defective Product scenario insurance was against a single contingency involving a possible $ 100,000 loss; in the Health scenario there was a tacit assumption that a single person would not undergo complications associated with the medical treatment more than once or that there would be any dependence in this respect between the different people in the health plan; and so on. In the Computeez scenario, however, we deliberately manipulated both the size of the potential loss (10,000 versus 100,000 units) and whether the occurrence of the insured event was independent from unit to unit or systematic (i.e., involved correlated events). This manipulation was designed to see how the size of the potential total loss (aggregating across units insured) would interact with ambiguity in affecting prices. As noted in Section 3.5, ambiguity did interact with size of total loss as represented by the number of units to be covered by the warranty. Specifically, whereas in the nonambiguous case the

average cost of the warranty per unit did not differ between the conditions involving 10,000 and 100,000 units, there was a significant differential effect in the ambiguous case where the prices per unit were, on average, some 35% higher in the latter. Ambiguity did not, however, interact with type of risk (independent or correlated) although the latter did affect prices significantly (both taken singly and by interacting with the probability level variable). The issue of how ambiguity interacts with the size and type of potential losses is important and requires more attention in future work.

4.3 *Some implications for the study of insurance markets*

Economists have typically explained the operation of insurance markets by assuming that (a) both firms and consumers know the probabilities of losses, but (b) differ concerning their attitudes toward risk. Specifically, consumers are assumed to be more risk averse than firms such that they are prepared to suffer a certain loss (i.e., premium) that is paid to firms who are willing to accept risks. The ability of firms to take on such risks is presumed to lie both in the greater amount of assets at their disposal (relative to individual consumers) and the fact that, over a large number of cases, firms can assess bounds on the risks they accept. In economics, these notions are made operational by assuming that firms and consumers have different utility functions over wealth.

The results of the present study can be thought of as challenging three key aspects of this traditional account. First, we have shown that ambiguity about probability estimates is important to the prices that consumers are prepared to pay and firms are prepared to charge. Thus differences in willingness to pay versus charge for insurance can not be traced simply to differences in hypothetical utility functions (i.e., wealth levels and attitudes toward risk) but also result from differential reactions to the nature of uncertainty itself. Specifically, we believe that most insurance is contracted for contingencies involving low probabilities of losses in situations similar to box 2 of Figure 2 where, relatively speaking, consumers are ambiguous but firms are not. Moreover, note that this is the case for which the largest positive difference between the ambiguity functions of consumers and firms is to be found (see Figure 3), and to the extent that prices are directly related to ambiguity functions, where profits per unit of insurance coverage will be greatest.

Second, both the ambiguity model and the data presented here are consistent with the notion that firms are more sensitive to ambiguity than consumers. In other words, in the presence of ambiguity, greater "risk aversion" is exhibited by firms than by consumers.

Third, both the ambiguity model and the data presented here show that attitudes toward ambiguity can shift from aversion to preference with changes in probabilities of losses. This means that people cannot be thought of as having consistent "attitudes toward risk" that are captured by unique utility functions and that are independent of the level of the probabilities that risky events might occur.

In making these comments, we do not mean to imply that an understanding of ambiguity will unlock most of the secrets concerning why people do or do not buy or sell insurance of various types. On the other hand, our results do emphasize that ambiguity plays a large role in the operation of insurance markets that economists have ignored to date.

4.4 *Final comments*

The topic of ambiguity was introduced at the outset of this report by way of Ellsberg's paradox. This showed, that in the presence of ambiguity, subjective probabilities inferred from choices could not necessarily be assumed to obey the laws of probability theory. This, in turn, raises the question as to whether insurance prices that are subject to ambiguity effects are also "illogical" or "irrational".

We believe that these questions can be answered at two levels. At a micro level, where rational behavior is equated with strict adherence to certain economic principles and the rules of probability theory, it is possible to show that some (but not all) of the observed reactions to ambiguity are "irrational" or, at least, inconsistent with other behavior. On the other hand, in a broader context it is important to note that the reactions to ambiguity observed in this survey are systematic. Thus, to the extent that people do not persist in "unreasonable" behavior, we do not believe that observed reactions to ambiguity are necessarily irrational. Instead, we believe that ambiguity is an important determinant of risk and, as such, needs to be incorporated in models of rational, economic behavior.

out many supporting tasks with great efficiency.

As stated in the report, my colleagues Hillel J. Einhorn and Howard Kunreuther have been intimately involved with this project from the outset and have provided numerous inputs dealing with theoretical, methodological, and practical aspects of the survey. Indeed, this survey is part of our common work on issues concerning ambiguity and contains both figures and summaries of data that have appeared in our earlier work (see Appendix A).

Appendix A

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Appendix B

A note on the ambiguity model

The mathematical model relating the anchor probability, p, to the ambiguous estimate, S(p), can be derived as follows.

Let the adjustment to the anchor be represented by k such that S(p) is given by

$$S(p) = p + k. \qquad (1)$$

To allow for the effects of ambiguity, decompose k into two parts that capture forces favoring positive and negative adjustments, respectively. The positive force reflects the weight given to possible values of the probability above the anchor and is taken to be proportional to (1-p); the negative force reflects the weight given to values below the anchor and is proportional to p. In both cases, the constant of proportionality is a parameter θ that represents the amount of perceived ambiguity in the situation ($0 \leq \theta \leq 1$). That is, the effect of possible values of the probability above the anchor are modeled by $\theta(1-p)$, of those below by θp, and k is the net effect of the two adjustments from the anchor.

To account for the possibility that values above and below the anchor may be differentially weighted in imagination, adjust θp to the form θp^β where β ($\beta \geq 0$) represents one's attitude toward uncertainty in the circumstances. Thus, when $\beta = 1$, equal weight is given in imagination to values above and below the anchor; when $\beta > 1$, more weight is given to larger values; and for $\beta < 1$, more weight is given to smaller values. This leads to the model

$$S(p) = p + \theta[(1-p) - p^\beta]. \qquad (2)$$

Note that in this model θ (i.e., perceived ambiguity) determines the amount of the adjustment, whereas β in conjunction with p determines its sign. As examples, all three panels in Figure 1 in the text have been drawn with the same θ parameter. However, in panel (a) $\beta < 1$, in panel (b) $\beta > 1$, and in panel (c) $\beta = 1$.

Appendix C

Scenario: The Defective Product
           Potential loss of $100,000 for a unique event

Table C.1

Median prices ($) of firms and consumers

Consumers

Probability of Loss	Actuaries		MBA Students	
	Ambiguous	Non-ambiguous	Ambiguous	Non-ambiguous
	$	$	$	$
.01	5,000	2,500	1,500	1,000
.35	42,000	40,000	35,000	35,000
.65	65,000	65,000	50,000	65,000
.90	75,000	90,000	60,000	82,500

Firms

Probability of Loss	Actuaries		MBA Students	
	Ambiguous	Non-ambiguous	Ambiguous	Non-ambiguous
	$	$	$	$
.01	5,000	2,000	2,500	1,000
.35	50,000	42,000	52,500	35,500
.65	80,000	69,000	70,000	65,000
.90	95,000	90,000	90,000	90,000

Notes
(1) The data for actuaries have been aggregated across 351 responses that involved several different sub-experiments.

(2) The data for MBA students involved 116 respondents. Each of these respondents gave prices for both the ambiguous and non-ambiguous versions of the scenario but in the role of either consumer or firm and at only one of the four probability levels.

Appendix C

Scenario: The Defective Product
Potential loss of $100,000 for a unique event

Table C.2

Percentages of respondents prepared to trade at given prices

Probability of loss = .01		$1,500		$3,000	
		Consumers %	Firms %	Consumers %	Firms %
Actuaries:	(n)[1]				
Ambiguous	(41)	100	16	86	32
Non-ambiguous	(37)	81	13	65	25
Other groups:[2]					
Ambiguous	(113)	87	17	83	40
Non-ambiguous	(139)	81	67	56	89

Probability of loss = .35		$37,500		$50,000	
		Consumers %	Firms %	Consumers %	Firms %
Actuaries:					
Ambiguous	(47)	82	16	32	64
Non-ambiguous	(45)	67	42	30	87

Notes

[1](n) indicates number of respondents per experimental condition of which approximately half played the role of consumers, and half the role of firms.

[2]Other groups included MBA students and executives attending management seminars (including a group of investment officers from life insurance companies).

Appendix C

Scenario: Brown River
Potential loss of $100,000 for possible annual event (flooding)
Ambiguity conceptualized as a restricted range: $.00 \leq p \leq .02$.

Table C.3

Median prices ($) of firms and consumers

Probability of loss = .01	Actuaries[1]		Student Groups[2]	
	Consumers $	Firms $	Consumers $	Firms $
Ambiguous	2,000	1,250	2,000	2,000
Non-ambiguous	2,000	1,150	1,200	1,000

Notes

[1]144 actuaries responded to this scenario.

[2]Respondents were 110 University of Chicago students and 163 students at the Wharton School.

Appendix C

Scenario: Brown River
Potential loss of $100,000 for possible annual event (flooding)
Ambiguity conceptualized as a restricted range: $.00 \le p \le .02$.

Table C.4

Percentages of respondents prepared to trade at given prices

Probability of loss = .01

	$ 1,100		$ 2,000		$ 2,500	
	Consumers %	Firms %	Consumers %	Firms %	Consumers %	Firms %
Actuaries:[1]						
Ambiguous	89	48	65	81	-	-
Non-ambiguous	100	44	79	75	-	-
Other groups:						
A. Students and executives[2]						
Ambiguous	88	36	-	-	47	89
Non-ambiguous	78	73	-	-	48	90
B. Executives[3]						
Ambiguous	68	41	45	62	-	-
Non-ambiguous	48	62	26	83	-	-

Notes
[1]Responses from 77 actuaries.
[2]These respondents included MBA students and business executives (186 in total).
[3]60 executives answered these questions.

Scenario: Palcam (warranty on personal computer)
Potential loss $400 per unit

Table C.5

Median prices ($) of firms (storeowners) and consumers

Actuaries (n = 239)	Consumers		Firms (storeowners)	
Probability of loss	Ambiguous	Non-ambiguous	Ambiguous	Non-ambiguous
.05	33	20	34	24
.25	105	100	120	125
.75	200	300	310	330

"Life officers" (n = 136)				
Probability of loss				
.05	25	20	40	20
.25	50	90	120	100
.75	100	200	300	300

Appendix C

Scenario: Computeez (price of a one-year warranty)
           Potential loss is $100 per unit
           Responses given on a per unit basis

Table C.6

Median responses ($)

10,000 units		Probabilities of breakdowns		
		.001	.010	.100
Ambiguous:	Independent risks	0.40	1.50	12.00
	Correlated risks	1.00	5.00	20.00
Non-ambiguous:	Independent risks	0.11	1.00	10.00
	Correlated risks	0.70	2.25	14.00

100,000 units				
Ambiguous:	Independent risks	0.50	2.00	12.00
	Correlated risks	1.00	12.85	25.00
Non-ambiguous:	Independent risks	0.12	1.05	10.00
	Correlated risks	0.10	1.24	12.25

Appendix C

Scenario: Health (complications following surgery)
Potential loss averages $100,000 per patient with complications
Responses: Minimum additional pure premium to be charged on
each of 100,000 people covered by the health plan.

Table C.7

Median responses ($)

Respondents in ambiguous condition

	$	(n)
Best estimate: .05 of 100 people	6.00	(11)*
.20 of 100 people	27.50	(26)
.50 of 100 people	75.00	(12)
Ranges: Between .00 and .10 of from 0 to 200 people	11.25	(27)
Between .10 and .30 of from 0 to 200 people	26.50	(22)
Between .40 and .60 of from 0 to 200 people	75.00	(21)

Respondents in non-ambiguous condition

	$	(n)
Estimate given as 5 out of 100 people	7.00	(17)
Estimate given as 20 out of 100 people	20.00	(21)
Estimate given as 50 out of 100 people	50.00	(22)

(n) indicates number of persons in experimental condition.

*In addition, 1 respondent indicated a refusal to insure.

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